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AN EMPIRICALLY-GROUNDED SIMULATION OF BANK DEPOSITORS

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ABSTRACT

There is a wide range of opinion regarding historical and theoretical causes of bank panics and financial crises. Current theory, and theory-based models, find little support in the historical record. This paper examines previous empirical findings based in detailed banking records and offers several new results based on detailed bank data from 1893 Helena, Montana. These findings suggest modeling bank panics as psycho-social events. The Bank Depositor Model (BDM) builds upon a model previously designed to examine emotions within a group (Bosse et al., 2009). BDM represents bank depositor behavior as resulting from a combination of heterogeneous agent (depositor) attributes, views expressed by those in an agents social network and exogenous events that may alter an agents receptiveness to positive or negative views. Initial results conform with the described empirical facts.

1 INTRODUCTION

In the United States the National Bank Era (1864 - 1913) was one of almost predictable crises with significant disruptions to the national banking system occuring in 1873, 1884, 1890, 1893 and 1907. The most severe disturbance, in terms of long term economic consequences as well as impact on the banking system, was 1893. In May of that year a wave of bank suspensions and closures began in the interior of the country, corresponding to the current day Mid-West. By the end of August more than 500 banks had shuttered at least temporarily and four years of economic problems began. While in many ways far less devastating than 1893, the Panic of 1907 resulted in a series of investigations and eventually the restructuring of the US banking system under The Federal Reserve Act of 1913.

There is little agreement as to the causes and mechanisms of such events. Financial crises exist within wide ranging economic and historical contexts. Theories are proposed, macro-level metrics are examined, and policy recommendations are made. Little in the historical record supports many of the claims made, either in theory or in policy. This paper presents results from an on-going research program that seeks to expand the empirical foundations upon which model-as-theory building can be based, as well as a model of bank depositors grounded in the historical record.

2 UNDERSTANDING BANK PANICS

2.1 Theories of Bank Panic

Current theories regarding the mechanics and causes of bank panics fall into two general categories, random factors and information asymmetries. The random factors approach, or sunspots as it is sometimes called, argues that bank runs or panics occur for completely random reasons. This theory posits that random exogenous events cause depositors to determine that the event or events that have occurred somehow cast doubt on the viability of certain banking institutions. This results in depositors withdrawing funds from institutions without regard for the the unknowable financial health of the institution. Asymmetric

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information reflects the idea that the knowledge of bank investment quality is asymmetric between the depositor and the bank. Therefore when an external shock that may reflect on the quality of a banks investment holdings occurs - such as a drop in key asset prices like commodities, real estate, or stocks - it is not known to what extent a given banks portfolio of investments is impacted. This can lead to a questioning of the solvency of banks perceived to be heavily invested in such assets, precipitating a generalized run on banks that may or may not have increased risk as a result of the external shock.

Both approaches seek to provide explanations of how rational depositors participate in a panic. Asymmetric information assumes some underlying truth, and a depositors imperfect view of that truth. Decision making, though rational, is confused by differences between the real and the depositors perceived risk at a given institution. In this respect the random factors theory is a limit point of asymmetric information, where no information is available, yet depositors still seek to act rationally to limit potential loss of savings.

Given the different perspectives on the origins of panic, the distribution of bank failures can be examined to determine which of the two approaches better fits empirical evidence. Policy implications associated with the differing origins can also be derived. For example, if the cause is a result of asymmetric information then policies that reduce the asymmetry would be prescribed, perhaps through public disclosure of a given banks investment portfolio or risk factors. While the information asymmetry is being reduced it may be necessary to support otherwise solvent banks that may suffer a run. If random factors were to blame, sources of liquidity should be provided to banks.

2.2 Theory-Derived Models

The most well known model of bank panics was developed by Diamond & Dybvig (Diamond and Dybvig 1983). Diamond & Dybvig describe a simple model of human decision making and develop the argument that this model can explain the manner in which bank runs may occur. Two kinds of depositors, patient and impatient are given one unit of wealth (endowment). Fear of losing a deposit, which is influenced by observing events and actions of other depositors, can cause bank runs. The model utilizes game-theoretic constructs, determining at what parameter settings equilibria representing panic occur. The purpose of the Diamond & Dybvig model was to examine the impact of depositor insurance. The authors found in their model that simply guaranteeing deposits eliminated any chance of a panic.

The basic Diamond & Dybvig model has been extended to introduce certain infromation asymmetries (Bryant 1980), asset shocks (Gu 2011), and cross-market contagion (Allen and Gale 2000). The analytic model of Diamond & Dybvig has also been used as the foundation of agent-based models (Romero 2007). In each case panics occur, i.e., agents withdraw significant amounts from the modeled banks, with some additional nuances based upon the particular addition to the basic model.

2.3 Historical Support for Extant Theories

Assuming information based origins, that customers have a lack of knowledge regarding individual bank solvency, one should witness broad-based runs correlated to specific exogenous events and not correlated with actual bank solvency. Such are the main findings of Calomiris & Gorton's analysis of crises during the National Banking period (Calomiris and Gorton 1991). They find that real economic shocks such as precipitous declines in stock prices, occurring at a time when banks are most exposed through increased loan demand, result in banking crises. The analysis is based on a macro analysis of nationwide bank closure data and stock prices. Dupont (Dupont 2007) presents a more detailed analysis of bank failures in Kansas during the Panic of 1893. In this study it is concluded that even with a great deal of publicly available information, bank runs did become contagious, arguing against the asymmetric information theory.

Carlson (Carlson 2005) offers that whether a given analysis is supportive of one theory or another depends on whether the data is aggregated or specific to a particular bank. Wicker (Wicker 2006) concludes that panics of the National Bank era showed evidence of both explanations, and banking problems in 1884 exhibited features consistent with *both* explanations.

Examination of higher frequency data, and a deeper investigation of data from the interior of the United States, suggests that evidence for both theories can be found, sometimes within in the same crisis. We are lead to this unsatisfactory conclusion - Both explanations may apply to varying degrees, or may not apply at all.

3 EMPIRICAL DETAILS OF BANK PANICS

3.1 Previous Empirical Analyses

Examination of the actual behavior of bank depositors during a run or panic is relatively uncommon. In modern cases there is a lack of publicly accessable data. For earlier episodes, bank records of necessary detail are rare. However, there is an emerging literature examining such events.

3.1.1 New York - 1854 and 1857

Examination of Irish immigrants and their behavior during the Panics of 1854 and 1857 showed a very strong correlation between depositors who “panicked”, i.e., closed their accounts, and the province of origin in Ireland (Kelly and O’Grada 2000). This correlation is shown to be associated with the tight knit, county and province centered social networks maintained by Irish immigrants in New York City. It is also demonstrated that withdrawals were not all or nothing. Some customers withdrew only part of their deposits, hedging against loss. Ó Grada & White (O’Grada and White 2003) provide a detailed analysis of the difference between behaviors in 1854 and 1857, arguing that 1854 more resembled random withdrawal and 1857 asymmetric information. We have, then, evidence of panics driven specifically by contagion through social networks and panics driven by those who fear losses based upon information regarding perceived portfolio weakness.

3.1.2 Gujurat, India - 2001

In a more modern setting Iyer & Puri (Iyer and Puri 2008) examined detailed deposit information for a Gujurat, India bank that suffered a run of deposits in early 2001. The run was triggered by the failure of a major financial institution in Gujurat. The run on deposits from other banks did not result in any closures or suspensions and the economy of Gujurat, and India in general, was doing well at the time. It is hence described as falling into the random factors category of crises rather than asymmetric information. It is shown that there was some correlation of running based upon ethnicity (i.e., Hindu vs. Muslim), home address and the fact that depositors needed an existing customer to refer them in order to open an account. Long-standing customers who had relationships that extended beyond simple savings or checking accounts were far less likely to run. Such customers were shown to help stop runs within their social network. This suggests that the more dimensions in the relationship between a bank and its customers, the more likely it is for the customer to decide not to go elsewhere with their business. The findings suggest a more nuanced explanation of the detailed mechanics of bank runs than is found in either of the dominant theories.

3.2 Helena, Montana - 1893

Placed in time between the New York City panics of 1854 and 1857 and the localized bank runs experienced in India in 2001 is the Panic of 1893. Ramirez (Ramirez 2009) refers to the Panic of 1893 as the “Perfect” panic to investigate the long term impact of bank crises. It was devestating economically, bank failures were widespread, and there appears to be little agreement as to the cause of the panic (Carlson 2005). During the National Banking Era there was far less regulation compared with more modern banking systems, there was no deposit insurance, and there was no central or coordinating national bank system as would be created by the Federal Reserve banks. Disclosures of information to both the government and to local clearing houses were limited and the only compelling power given to the Comptroller was the revocation of a banks charter, a "death penalty" that was rarely used. It was, in many ways, as close to free market banking as would be achieved in the United States.

An additional factor that makes the Panic of 1893 of significant interest - the existence of a massive and relatively untapped data repository in Helena, Montana. In the archives of the Montana Historical Society are more than three hundred linear feet of ledgers containing the records of four national banks operating in Helena. This collection provides daily data for all four banks for the entire history of each bank. Included are daily balance sheet, time certificate, and demand deposit records. Also included are many thousands of letters and other forms of correspondence. This repository allows investigation in many dimensions, including the day-to-day actions of depositors as well as the day-to-day conditions and operations of each bank. Data regarding the two largest banks, Merchants' National Bank of Helena and 1^{st} National Bank of Helena, are described in this section. By size 1^{st} National was in the top 3.5% of all national banks, Merchants' in the top 7%. Findings presented for Merchants' are contained in MC115, Volumes 80, 81, 93, 94 and 206. For 1^{st} National, MC 116, Volumes 45, 46, 48 and 50. Much of the data used in this study focuses on the first 7 months of 1893. 1^{st} National would suspend on July26, 1893, reopening in January of 1894. Merchants', though under significant stress, would remain open.

3.2.1 Endowments of Individual Accounts

On June 1, 1893 Merchants National Bank had 1255 outstanding Time Certificates owned by 615 unique individuals with a total value of $1,137,082. Time certificates were the largest form of deposit for the four national banks in the Helena archives, and amounted to more than 85% of personal deposits at Merchants during the period from May 1 to July 31 of 1893. It was often the case that a customer owned more than one time certificate. Breaking up savings into more than one certificate reflected availability of cash for deposit over time and also allowed flexibility without having to pay a significant penalty if the customer had unexpected cash needs during the period of a given time certificate.

On the 1st of July in 1893 Merchants National Bank also had 482 customers maintaining a positive balance in their Demand Deposit accounts. These accounts were normally used as a way to conduct business, similar to current checking accounts, and did not pay interest. Individuals and business owners associated with the demand deposit accounts have yet to be compared with time certificate owners to determine the total individual holdings for each bank customer.

Figure 1 shows a log-log plot of the ranked list of time certificate owners and demand deposit account balances. Although much work remains to be performed on this data it is clear that the balance amounts for both types of deposit are skew.

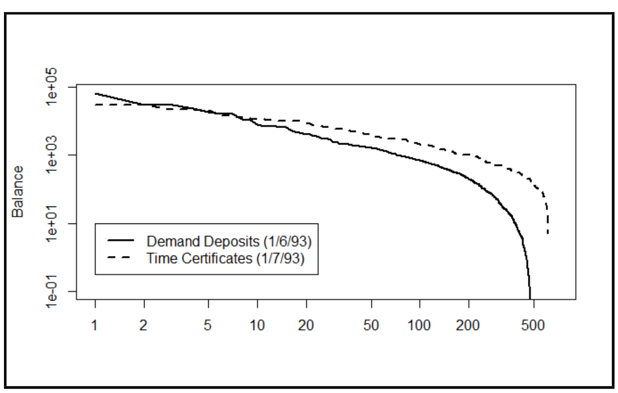

Figure 1: Deposits Ranked by Size, Merchants' National Bank

3.2.2 Daily Change in Bank Deposit Levels

On 3 January, the first business day of 1893, total deposits at the two largest banks, 1^{st} National and Merchants, amounted to \$2,839,529 and \$1,372,978. Figure 2 shows the percentage change in total deposits for the two banks from 3 January, 1893 to 26 July, 1893, the eve of 1^{st} National's suspension. It is interesting to note that 1^{st} National suffered far less loss of deposits percentage-wise than Merchants', 17.6% versus 26.4%, yet was compelled to suspend when cash on hand dwindled. Additionally, the run on deposits at Merchants' began in early January versus mid-April for 1^{st} National.

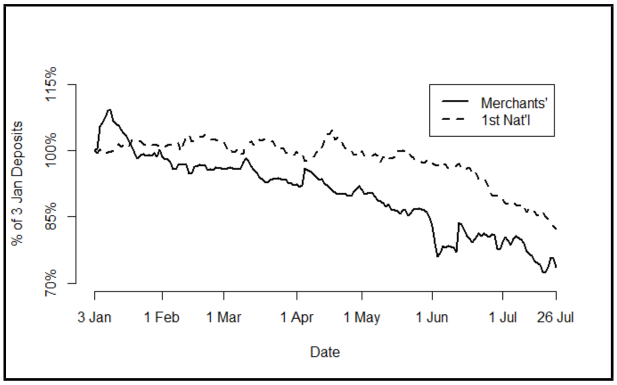

Figure 2: Percent of Total Deposits, 3 Jan 1893 = 1.0

During the period of 26 January 1891 to 26 July 1896 there were 761 business days for banks in Helena. Figure 3 shows the frequency distribution of the daily growth rates for total deposits in Merchants' and 1^{st} National over this period. Visually the data describes an exponential (or Subbotin) distribution. Such distributions have been found to occur in other economic growth rate data including monthly and quarterly GDP and IP growth rates in OECD countries (Fagiolo, Napoletano, and Roventini 2006) and annual firm growth rates in the United States (Perline, Axtell, and Teitelbaum 2006), in which the distribution is shwon to be more specifically an asymmetric exponential distribution.

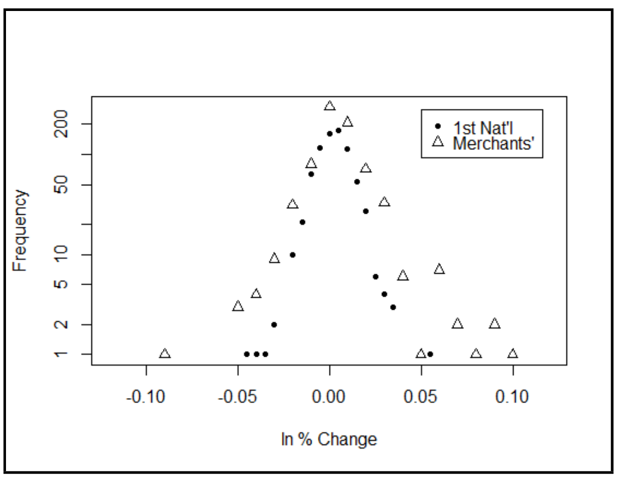

Figure 3: Daily Change in Total Deposits, 26 Jan 1891 - 26 July 1893

3.3 Empirical Findings

Several empirical facts regarding bank panics are established in Section 3.1.

1. Behaviors, such as those that occur in a panic, are contagious and can be self-reinforcing.
2. The contagion spreads via a social network.
3. Agents with high social capital exert disproportionate influence over others.
4. Exogenous events cause changes in the way depositors interpret information and can result in spirals or panics.

From the Helena data can be added two more findings, specific to the Panic of 1893.

5. Deposit amounts are skew distributed.
6. Daily growth rates of bank total deposit levels are distributed in an asymmetric exponential fashion.

These findings prescribe certain features to be included in a model of bank customer behavior, structure of input data for such a model, and also provide metrics to test the outputs of such a model. The simplicity of the Diamond-Dybvig model is appealing. For specific abstract questions the model has provided interesting insights. Stylized facts, such as "panics occur", and "panics are contagious" are reproduced in some form, with little attempt to determine if bank or depositor level results of the model are recognizable in the historical record. These limitations are affirmed by Eric Smith and Martin Shubik (Smith and Shubik 2012), who extended Diamond-Dybvig by implementing the noise model of Stephen Morris and Hyun Song Shin, and utilizing evolutionary game theory approaches to do sensitivity analysis of both the basic and extended Diamond-Dybvig models. Smith & Shubik suggest perhaps the limits of the *homo ludens* approach has been reached. Their summary is telling, "... when confronted with items such as incomplete knowledge of the rules of the game and a multiplicity of socio-psychological phenomena to account for we are still far from understanding context and dynamics."

4 THE BANK DEPOSITOR MODEL (BDM)

Sawyer (Sawyer 2005) defines two approaches used in the agent-based modeling community, the *cognitive* and *reactive* approaches. Diamond & Dybvig is a cognitive model, positing a specific agent decision making process focused on optimizing individuals outcomes. What is proposed here is a reactive approach, where changes in deposit levels, customer behaviors, are driven by external events and the shared views of those in an agents neighborhood. There is no attempt at individual optimization or calculation of a best course of action.

Bosse et al. (2009) proposed an agent model of the emotional contagion process described in more general terms by Barsade (Barsade 2002). The model provides mechanisms for contagion as well as spiraling emotional levels as observed in group settings (Barsade 2002) (Frederickson and Joiner 2002). The Bank Depositor Model uses the Bosse model as analog for bank depositor actions. Consistent with social influence network theory, the emotional level of an agent is linked to the agents actions as a depositor (Friedkin 2010). As agent emotion becomes more positive, a greater share of the agents endowment is deposited. As it decreases, less is deposited. In the case of the BDM there is a clear linkage between emotional spirals and behavioral spirals, or panics.

4.1 Model Specification

The following is a formal specification of the Bank Deposit Model.

1. Define A, a set of agents. Each agent $a \in A$ has attributes:
   (a) $q \in [0, 1]$, agent's emotion or outlook level.

(b) $\varepsilon \in [0, 1]$, extent to which the agent expresses their emotion to social contacts.
(c) $\delta \in [0, 1]$, agents openness or sensitivity to received emotions.
(d) $\beta \in [0, 1]$, agents tendency to adopt emotions positive or negative.
(e) $w \in R^{+}$, the endowment or wealth of the agent.

2. Define $L = \{l_{i,j}\}$, a set of directed links, where $l_{i,j}$ denotes a link connecting agent i to agent j.
   (a) Each link $l_{j,i}$ has strength $s_{j,i} \in [0, 1]$ which expresses the degree to which agent j's current outlook is communicated to agent i.
3. For agent a_i the set $N_i = \{j \in A \mid \exists \text{ link } l_{j,i} \in E \text{ for } i \text{ and } j\}$ in the set of in-links, or neighborhood.

The agent attribute q refers to the expressed emotion or position of a depositor. It is assumed that this expressed emotion is equivalent to the actions taken by the depositor, i.e., that there is no deception involved. Values closest to 1 suggest totally supportive or positive relative to the placement of investments or savings with a financial institution, near 0 mean unsupportive.

The variable ε, or expressiveness, describes the level or degree to which an agent expresses their emotion or position. A value of 1.0 indicates an agent that expresses their opinion constantly and to everyone they connect to, a true extrovert. A value close to 0 indicates someone who rarely if ever communicates their views to the outside world.

δ indicates an agents openness to the opinions of others, as measured by the rate at which agents adopt the views of others as their own. A value of 0 indicates an agent who will not change their mind under any circumstances. A value of 1.0 indicates an agent who will quickly take a position consistent with the combined opinions of their neighbors.

β indicates the overall inclination of an agent to process and accept positive or negative news or emotions. A value of 0.5 indicates a depositor who interprets negative and positive emotions equally. A value of 1.0, only positive views are considered, 0.0 indicates only negative.

At each time step the model computes the change in the emotion level of an agent, q_i, based upon interaction with agents in its neighborhood, N. The change in q_i per given time period t for agent i is computed as follows:

$$\frac{\Delta q_i}{\Delta t} = \gamma_i[\beta_i(1-(1-q_i^*)(1-q_i)) + (1-\beta_i)q_i^* q_i - q_i]. \tag{1}$$

Where

$$\gamma_i = \frac{\sum\limits_{j \in N_i} e_j s_{j,i} \delta_i}{\mid N_i \mid}, \tag{2}$$

is the normalized sum of the magnitude at which a given emotional level would be received by agent i. Equation 2 differs from Bosse et al. Normalizing the value by dividing by $\mid N_i \mid$ is necessary to avoid a value of $\frac{\Delta q_i}{\Delta t}$ greater than β_i.

$$q_i^* = \frac{\sum\limits_{j \in N_i} \varepsilon_j s_{j,i} q_j}{\sum\limits_{j \in N_i} \varepsilon_j s_{j,i}}, \tag{3}$$

is the sum of the emotion values being transmitted to agent i, normalized by the sum of the level at which those emotions are being communicated. After $\frac{\Delta q_i}{\Delta t}$ is computed for each agent, all agents apply the changes to q_i, then time is incremented.

4.2 Exogenous Events

Exogenous events are used to impact the general outlook of an agent, to determine if they are more or less receptive to a given view as expressed by those in their neighborhood. This is the only stochastic element of the simulation. An event can be positive or negative and is reflected in a change to the β value of each agent. The exogenous event process is implemented as follows:.

1. $E \in [0, 1]$, the probabilty that for any given time step an exogenous event will occur
2. $min \in [-1, 1]$, the lower bound on the impact of an exogenous event
3. $max \in [min, 1]$, the upper bound on the impact of an exogenous event
4. $P_{max} \in [0, 1]$, the maximum probabilty that a given event will impact a given agent

If, for a given time step, an event has been determined to have occurred (as per a random draw against E), execute the following logic.

1. Let C = U[min, max], the impact the event will have on susceptible agents
2. Let p = U[0, P_{max}], the probability the event will impact any given agent
3. For each agent a_i with U[0, 1] $< p$
   (a) If $C < 0$, then $\beta_i' = \beta_i(1 + C\delta_i)$
   (b) If $C > 0$, then $\beta_i' = \beta_i + (1.0 - \beta_i)C\delta_i$

4.3 Steady States

Equation 1 indicates that for an agent with β = 1, $\frac{\Delta q_i}{\Delta t} \geq 0$, and is equal to zero only when all agents in the neighborhood have $q \equiv 0$. Additional steady states can be shown to occur when $\beta_i \equiv \beta$, for some β, and $q_i \equiv q$, for some value q. In this case the following can be shown to be true.

1. If β = 0.5, the system is in a steady state.
2. If q = 0.0 or 1.0, the system is in a steady state.
3. If $\beta < 0.5$, then $\forall i, q_i \Rightarrow 0.0$ over time.
4. If $\beta > 0.5$, then $\forall i, q_i \Rightarrow 1.0$ over time.

5 Results

5.1 Scenarios

The four scenarios used in this study share several common features.

1. Section 3.3, Finding #5 indicates that the distribution of endowments is skew. For all scenarios endowments are set using a Zipfian distribution, where w = 10,000 / i.
2. All scenarios use 500 agents, arranged in a small world architecture connecting the 5 neighbors to each side of an agent and with a 0.1 probability of rewiring a given link.
3. Section 3.3, Finding #3 establishes that higher social capital agents have higher influence than those with less capital. In this study endowment, i.e., wealth, is used as a surragate for social capital. The strength of a link from agent i to agent j computed as:
$$e_{i,j} = \frac{1}{2}\left(sgn\left(\frac{w_i - w_j}{W_{max}}\right) \left|\frac{w_i - w_j}{W_{max}}\right|^{S_{fac}} + 1.0 \right). \tag{4}$$
4. All scenarios were executed over 10 iterations, for a duration of 25,000 time steps, and total bank deposits reported every 20 time steps and computed as:
$$M(t) = \sum_{a \in A} w_i(t) q_i(t). \tag{5}$$
5. All scenarios and cases utilize the same random number stream. Within a case, each iteration uses different streams.

Scenarios 1, 2 and 3 utilize the same exogenous event parameter set, where $E = 0.05$, $P_max = 0.05$, $min = -0.15$ and $max = 0.15$. In Scenario 4 events are skewed to represent more negative than positive news where $min = -0.20$ and $max = 0.10$.

Each scenario has randomly selected rewiried links, and in the case of Scenario 1, randomly ordered agents. For each Scenario 3 cases were generated to examine the impact of randomness in the initial networks.

Table 1 identifies the differences between the four model scenarios used in this study.

Table 1: Scenarios

Scenario	Features
Scenario 1	All agent q_i, ε_i, δ_i and β_i initialized at 0.5. Agents arranged randomly before links are assigned.
Scenario 2	All agent q_i, ε_i, δ_i and β_i initialized at 0.5. Agents arranged based on endowment.
Scenario 3	Agent q_i, ε_i, δ_i and β_i initialized using a triangular distribution with min = 0.0, max = 1.0, mode = 0.5. Agents arranged based on endowment.
Scenario 4	Same as Scenario 3 except with different exogenous event probabilities, as described above.

5.2 Model Results

Model results are focused on two specific claims made. First, depositors should show herding or spiraling behavior disproportionate to the magnitude of the exogenous events. This will demonstrate the fragile nature of bank depositor confidence under certain situations. Second, bank-level deposit amounts should fit the distribution discovered in empirical analysis.

5.2.1 Model Depositor Spirals

Spiraling can be observed by examining the output variable $M(t)$ for a given model run. Figure 4 shows sample outputs for a single run from each of the four scenarios. Scenario 1 demonstrates a collapse. The frequency of collapse by scenario is shown in Table 2. Each case in each scenario differs from the other in terms of which links are rewired in the social network. For Scenario 4, where all cases collapse, the difference lies in the time to collapse. The difference between Scenario 3 and Scenario 4 show the sensitivty of the system to bias in the exogenous events.

Table 2: Scenarios

Scenario	Runs	$\Rightarrow 0.0$	$\Rightarrow 1.0$	Avg. Steps to Collapse
Scenario 1	30	6	6	
Scenario 2	30	3	3	
Scenario 3	30	0	0	
Scenario 4 - Case 1	10	10	0	17506
Scenario 4 - Case 2	10	10	0	15140
Scenario 4 - Case 3	10	10	0	15454

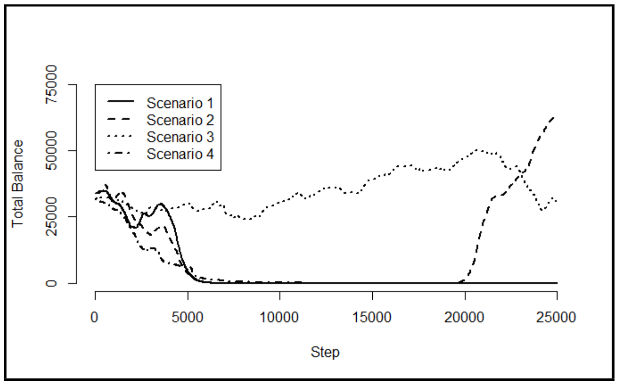

Figure 4: Daily Change in Total Deposits, Sample Run per Scenario

5.2.2 Model Bank Growth Rates

Scenarios were choasen to demonstrate different model functionalities and issues. Scenario 3 is the only scenario that consistently does not become pathological in the sense of collapsing confidence or overwhelming exuberance. Figure 5 shows the frequency distribution of the rate of change in total deposits for Scenario 3, using 20 steps as the time interval giving 1249 data points per iteration (one less than the number of reports since we are computing rate of change). The 3 iterations were selected one from each case, and intentionally chosen to have end of run values significantly different from each other. Hence they are illustrative of the variety of iteration outcomes in Scenario 3. The three iterations displayed all exhibit a distribution shape consistent with the findings of daily total deposit level changes in the two Helena banks. More extensive analysis of the detailed distributions are necessary but a prelliminary claim that the BDM generates outputs found in the empirical record seems reasonable.

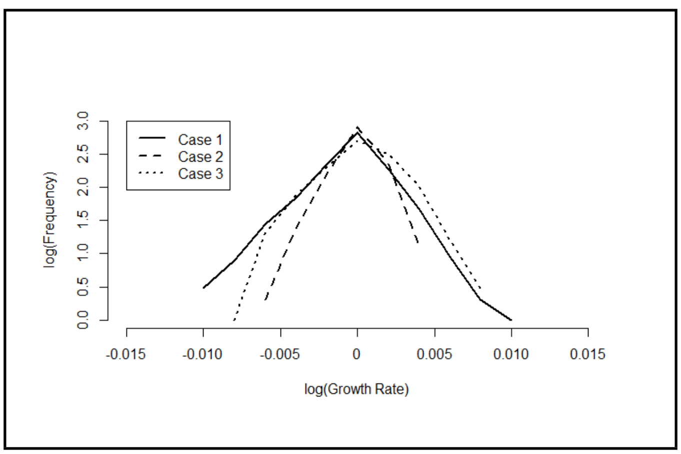

Figure 5: Distribution of Change in Total Deposits, 3 Runs, 20 step interval

5.3 Evaluating the Model

Social networks play a critical role in depositor actions, particularly during a crisis. Several scenarios have been developed to begin the investigation of how social networks impact bank solvency, in this case as represented by the total level of deposits in a bank. The model should, as a minimum, reflect the findings of Section 3.3. In the following, the method of capturing or representing the specific facts are established.

Many of the facts are modeled explicitly by the choice of the Bosse model as a foundation for the BDM, others through specific input data, and yet others as a result of model outputs.

1. *Behaviors, such as those that occur in a panic, are contagious and can be self-reinforcing.* Explicitly represented.
2. *The contagion spreads via a social network.* Explicitly represented.
3. *Agents with high social capital exert disproportionate influence over others.* Implemented in data, see Item #3, Section 5.1
4. *Exogenous events cause changes in the way depositors interpret information and can result in spirals or panics.* Basic effect is directly modeled. Section 5.2.1 shows that panics are disproportionate to magnitude of exogenous events.
5. *Deposit amounts are skew distributed.* Input data, as described in Item #1, Section 5.1.
6. *Daily growth rates of bank total deposit levels are distributed in an asymmetric exponential fashion.* Demonstrated in Section 5.2.2

6 CONCLUSIONS AND FURTHER RESEARCH

The goal of this research program is to use a bottom-up method to discover empirical facts based in higher frequency and more detailed data than has been used in developing current theories of bank panic origins and mechanics. This is accomplished by examining detailed depositor and bank actions using the detailed records at the Montana Historical Society Library. This is consistent with the micro to macro approach to understanding modern economic systems advocated by Farmer and Foley (Farmer and Foley 2009). The BDM, as presented, begins to move in the direction of these goals.

The Bank Depositor Model captures the observed features of bank panics. Further data development will allow additional analyses utilizing functionality currently available in the Bank Depositor Model. Current research is focusing on two items. First, the development of a historically accurate representation of bank customers for Merchants' National Bank. For each customer address, occupation and potential sources of social connectivity are being gathered. Given the scale of the project, more than 750 individuals and more than 100 firms at any given point in time, the effort will require significant further effort. However, when complete the data will provide the first empirically-grounded bank depositor data set for use in projects similar to BDM.

The second research area involves extending the Bank Dpeositor Model to represent more than one bank. It can be shown that bank-to-bank relaitonships played a critical role in maintaining or disrupting solvency during the Panic of 1893. Significant balances were maintained at correspoding banks. It has also been demonstrated that contagion effects between the four Helena banks were significant (Ramirez and Zandbergen 2013). The expected result will be a model that can examine the impact of social networks on such contagion, and to capture the possibility of regional banking crises spreading to other parts of the National Bank system.

The work presented represents an initial description of a much larger research agenda focused on developing models that can capture many of the complexities of banking. Although limited in scope, several significant empirical facts not represented in or generated by previous models are captured in the Bank Depositor Model.

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